

GET JOURNAL OF  
& **B**IOSECURITY  
**O**NE HEALTH

**PUBLISHED BY:**

**Global Emerging Pathogens  
Treatment Consortium**

**JOURNAL WEBSITE**

[www.getjournal.org](http://www.getjournal.org)

# Mapping the Spatial Prevalence of Disease Using a Community-Centric Approach with Hexagonal Grid Tessellation: A Case of CKDu Incidences in Northern Yobe State, Nigeria

\*<sup>1,2</sup>Babagana-Kyari M, <sup>3,4</sup>Yaro NA, <sup>4</sup>Kabiru MY

<sup>1</sup>Department of Environmental Health and Safety, School of Health Sciences, Maryam Abacha American University, Maradi, Niger

<sup>2</sup>Centre for Environmental and Geographical Research, Yobe State University, Damaturu, Yobe State, Nigeria

<sup>3</sup>Department of Geography, Northwest University, Kano, Nigeria

<sup>4</sup>School of Public Health, Maryam Abacha American University of Nigeria, Kano

\*Corresponding Author: Modibbo Babagana-Kyari

Phone: +2348030502141

ORCID: <https://orcid.org/0000-0002-8740-5494>

## ABSTRACT

Chronic Kidney Disease of unknown etiology (CKDu) poses a major public health challenge in Northern Yobe State, Nigeria, particularly in settings characterized by limited geocoded health records and weak disease surveillance systems. In such data-poor contexts, alternative methodological approaches are required to understand disease distribution and guide etiological investigations. This study demonstrates how CKDu spatial prevalence can be examined using a community-centric, GIS-based approach that relies on surveys of diagnosed CKD cases within victim households in a CKDu-endemic region of Yobe, integrating participatory data collection with open-source geospatial tools. Household-level data were collected through electronically administered questionnaires deployed via the KoboToolbox platform, supported by community leaders and implemented through snowball sampling over a 28-day period. Spatial analyses, including hexagonal grid-based tessellation, hotspot mapping, kernel density analysis, and spatial autocorrelation, were employed to visualize and quantify disease clustering. CKD incidence counts were aggregated within a uniform hexagonal grid, and spatial variability was classified using standard deviation-based incidence density categories to identify statistically meaningful concentration patterns across the study area. The analysis identified three distinct hotspots categorized by disease incidence density levels: high (7–10 cases), medium (3–6 cases), and low (1–2 cases). Spatial statistics derived from Moran's I index yielded a value of 0.1046, with a z-score of 4.95 and a *p*-value of 0.000001, indicating a less than 1% probability that the observed clustering of CKD incidences occurred randomly. Overall, the findings demonstrate that CKDu occurrence in Northern Yobe State is spatially non-random and can be effectively characterized through GIS-based, community-centric approaches in data-constrained regions. Thus, by generating spatially explicit evidence from diagnosed household cases, this methodology provides a robust foundation for targeted exploration of environmental risk factors and supports informed public health surveillance, environmental management, and policy interventions aimed at uncovering the aetiology of heightened CKDu prevalence in Northern Nigeria.

**Keywords:** Tessellation; Disease mapping; CKDu; Spatial prevalence; Qfield survey; Bade CKD

Corresponding Author's Email: [Modibbobgk@gmail.com](mailto:Modibbobgk@gmail.com)

## INTRODUCTION

Chronic Kidney Disease of unknown Etiology (CKDu) has emerged as a significant global public health concern, predominantly affecting rural agricultural communities situated in tropical and subtropical regions [1]. This disease is characterized by its huge impact on young to middle-aged populations, and notably occurs in the absence of conventional risk factors such as diabetes mellitus and hypertension [2]. The disease presents a complex and poorly understood epidemiological pattern, underscoring the urgent need for intensified research efforts to elucidate its etiology, risk factors, and effective prevention strategies. Against this backdrop, Chronic Kidney Disease of unknown etiology (CKDu) has become a pressing issue, primarily due to its unidentified causative factors. Unlike traditional CKD forms, which are typically associated with well-established risk factors such as diabetes, hypertension, and other known etiologies [3]. CKDu predominantly affects rural agricultural communities in developing nations. Its frequent clustering suggests that environmental and occupational exposures play a central role in its occurrence [4]. In Northern Yobe State, Nigeria, CKDu has become a rising public health concern, mirroring trends observed in similar settings.

However, the absence of geocoded hospital-based data and incomplete diagnostic records significantly impede accurate spatial epidemiological analyses in Nigeria. For instance, a study assessing the performance of health information systems in Ondo and Ekiti States revealed considerable gaps in data accuracy and completeness, with data accuracy reported at 70.1% in Ondo and 40.4% in Ekiti, and data completeness at 82.9% and 44.2%, respectively [5]. Similarly, a retrospective review of inpatient health records at the Federal Medical Centre, Bida, indicated that while prompt documentation was high (98.49%), the utilization of discharge summary forms was notably low (12.84%), and proper entry of patients' details stood at less than 60%, highlighting serious deficiencies [6]. These deficiencies emphasize the necessity of adopting community-based, geospatially assisted approaches to obtain more specific and contextually accurate health data for research, particularly in semi-urban settings where such data are readily lacking. The challenge is further exacerbated by the lack of geospatial information, such as accurate patient address data, which is critical for revealing spatial patterns and associations between CKDu incidence and environmental determinants [7]. This limitation obstructs effective spatial analysis and makes it difficult to investigate potential risk factors like water quality and agricultural activities, which are known to vary across different locations in Northern Yobe State.

Addressing this data gap necessitates the adoption of community-based strategies that actively involve local populations in disease surveillance. Such approaches have proven effective in enhancing data collection and reliability, as demonstrated by [8] in their research on colorectal cancer in Iowa. Engaging community members in identifying and reporting CKDu cases enables researchers to develop a more comprehensive and accurate representation of the disease's spatial distribution. Similarly, GIS-fluent approaches have been shown to improve health outcomes in low-resource settings, where access to healthcare services is often limited. For instance, successful initiatives include dengue disease surveillance in developing countries conducted by [10], as well as the containment of bovine paralytic rabies outbreaks in rural Mexico [11]. Collectively, these examples highlight the value of community engagement in addressing emerging public health challenges.

Despite these demonstrated benefits, public health interventions frequently fail to adequately prioritize high-incidence areas. In Nigeria, for example, several studies have shown that malaria control programs have historically focused on urban centers, even though higher transmission rates persist in peri-urban and rural communities [12]. Such patterns reflect broader systemic challenges in translating spatial epidemiological evidence into spatially equitable public health responses. To address these limitations, integrating community-centric approaches with Geographic Information Systems (GIS) offers a robust and effective solution. GIS has significantly advanced health research by enabling the visualization and analysis of spatial epidemiological data, thereby improving understanding of disease distribution patterns, associated risk factors, and resource allocation strategies. During the COVID-19 pandemic, for instance, GIS tools were critical in tracking infection hotspots, forecasting disease spread, and informing public health interventions globally [13]. Similarly, GIS-based malaria mapping has played a key role in identifying transmission zones and guiding targeted vector control efforts in sub-Saharan Africa [14].

Beyond infectious diseases, GIS applications in health research include mapping and modeling the spatial distribution of cardiovascular conditions and their associated risk factors [15]. GIS has also been used to analyze mosquito distributions and their environmental determinants, supporting the design of vector-borne disease control strategies and targeted public health campaigns [16, 17, 18]. In resource-limited settings, open-source GIS platforms provide cost-effective tools for collecting, managing, and analyzing spatial data [19]. These platforms enable the mapping of CKDu prevalence alongside environmental

variables such as water quality, agricultural practices, industrial activities, and other comorbidities suspected to contribute to CKDu incidence [20, 21, 22]. Through this spatial approach, researchers can identify geographic clusters or “hotspots” of CKDu, thereby highlighting areas with significantly elevated disease burden for targeted investigation and healthcare intervention.

Against this backdrop, the present study integrates GIS technology with a community-driven data collection approach to provide a comprehensive analysis of the spatial prevalence of diagnosed CKDu in Northern Yobe State. By identifying disease hotspots, the study seeks to enhance understanding of CKDu spatial distribution patterns while also assessing the effectiveness of the applied community-centric, GIS-based methodology.

## METHODOLOGY

### Study Area

The study was carried out in Northern Yobe State, Nigeria, focusing specifically on Bade Local Government Area, a semi-arid region characterized by a fragile ecosystem, heavy reliance on groundwater resources, and extensive agricultural practices. The environmental landscape presents several risk factors potentially linked to the emergence and prevalence of Chronic Kidney Disease of unknown Etiology (CKDu). Notably, communities depend heavily on shallow wells, boreholes, and informal water sources, which are often susceptible to contamination by naturally occurring nephrotoxic elements such as fluoride, heavy metals (example, cadmium, arsenic, lead), and nitrates. Additionally, the widespread use of agrochemicals, including fertilizers and pesticides, in irrigation farming raises concerns about the leaching of toxic substances into groundwater supplies [23]. Combined with climatic stressors such as high temperatures and prolonged dry seasons, which can exacerbate dehydration and concentrate pollutants, these factors create an environmental backdrop conducive to renal stress and potential CKDu development [24]. Thus, the interplay between groundwater quality degradation, agricultural intensification, and climatic vulnerability forms the critical environmental context underpinning the disease risk landscape in the study area. The study area was purposively selected due to the high endemicity of rampant cases of the disease CKD [25, 26]. This region is an arid and semi-arid region known for its harsh environmental conditions.

The area is characterized by open water bodies (rivers), extreme heat waves, and intensive paddy rice agriculture and fishing activities, which serve as a primary livelihood for the local

population. It is a riparian community along the river Yobe, in Northeastern Nigeria (Figure 1).

Bade Local Government Area (LGA) is strategically located in Yobe State, sharing its northern boundary with Nguru and Karasuwa LGAs and its eastern border with Jakusko LGA. The central town, Gashua, serves as both the administrative and economic hub of the region, located at approximately latitude 12°52'N and longitude 11°03'E. The town's pivotal role underscores the region's socioeconomic significance in Northern Yobe.

In Bade, groundwater serves as a primary source for domestic consumption and irrigation, yet its quality and availability pose significant public health concerns. The region's water resources are often limited and prone to contamination, raising concerns about safe drinking water access [27]. Persistent droughts and insufficient water infrastructure exacerbate these risks, creating a challenging environment for the population [28]. These conditions are suspected to contribute to the increased prevalence of chronic kidney disease of unknown etiology (CKDu) in the area [29]. Additionally, the widespread use of agrochemicals and fertilizers in farming further intensifies potential environmental health risks in the region. Many farmers in Northern Yobe heavily rely on these substances to enhance crop yields, inadvertently exposing themselves and the surrounding environment to hazardous chemicals [30]. This intensive agricultural practice is considered a contributing factor to the region's rising CKDu cases [31, 32]. Moreover, Bade experiences a semi-arid climate with distinct seasonal variations. The short rainy season occurs between April and October, while the prolonged dry season extends from November to March. The flat terrain, interspersed with undulating surfaces, features seasonal rivers that temporarily support farming and livestock activities during the wet season. Proximity to the Yobe River enhances agricultural opportunities, including fishing and irrigation. However, the semi-arid Sahelian conditions, characterized by sparse vegetation and drought-resistant flora, define the broader ecological framework [33].

The local economy primarily depends on subsistence farming and livestock rearing, both of which are significantly hindered by limited rainfall and challenging climatic conditions [34]. Gashua serves as the economic hub, linking rural communities to larger markets and supporting trade and resource distribution. The interplay between climate, terrain, and economic practices shapes the socioeconomic adaptations of Bade's population. Traditional farming and pastoral practices remain the cornerstone of livelihood strategies, deeply rooted in the region's environmental realities.

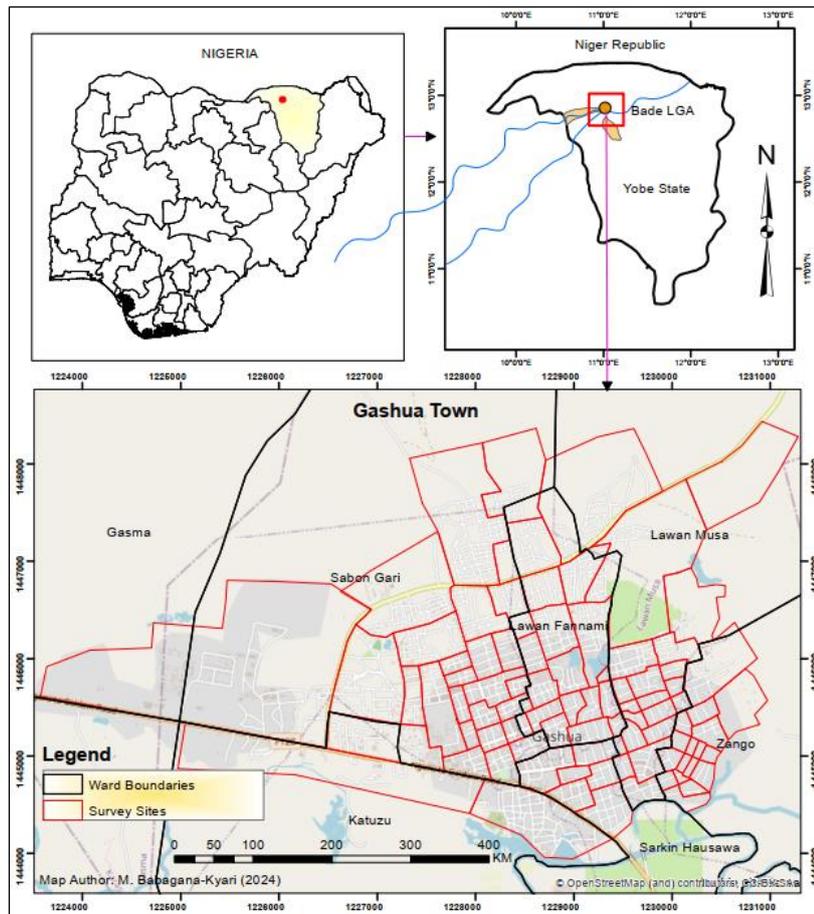


Figure 1: Study site map in Northern Yobe

Geologically, Bade lies within the Chad Basin, characterized by sedimentary formations comprising Quaternary and Tertiary deposits. These deposits, composed primarily of alluvial sands, silts, and clays, result from Ancient River and lake systems that once traversed the region. Wind-driven Aeolian processes have contributed to the formation of ancient sand dunes, particularly in the northern parts of the area [35]. These sedimentary layers support shallow aquifers, which play a critical role in sustaining water supply during the dry season, as surface water sources are scarce.

Additionally, the sedimentary geology underpins local hydrology and land-use patterns, shaping both agricultural and water resource management practices [35]. In conclusion, Bade's unique environmental, climatic, and geological features create a complex interplay of opportunities and challenges. While the region benefits from its rich natural resources and traditional adaptation strategies, issues such as water scarcity, agrochemical use, and climate variability present significant risks to public health

and socioeconomic development. These factors necessitate targeted interventions to ensure sustainable management of resources and improved health outcomes for the population.

### Research Approach

This study adopted a community-centric approach integrated with geospatial analysis to examine the spatial prevalence of Chronic Kidney Disease of unknown aetiology (CKDu) in Northern Yobe State, Nigeria (Figure 2). The approach was operationalized through active engagement of community leaders, health workers, and traditional authorities, who supported participant mobilization and household recruitment. Community sensitization meetings were conducted prior to data collection to explain study objectives, build trust, and obtain informed consent.

Selected community volunteers were trained to assist in administering structured surveys, identifying medically confirmed CKDu-affected households, and supporting participatory mapping using GPS-enabled tools, including the QField and KoboToolbox applications. This participatory

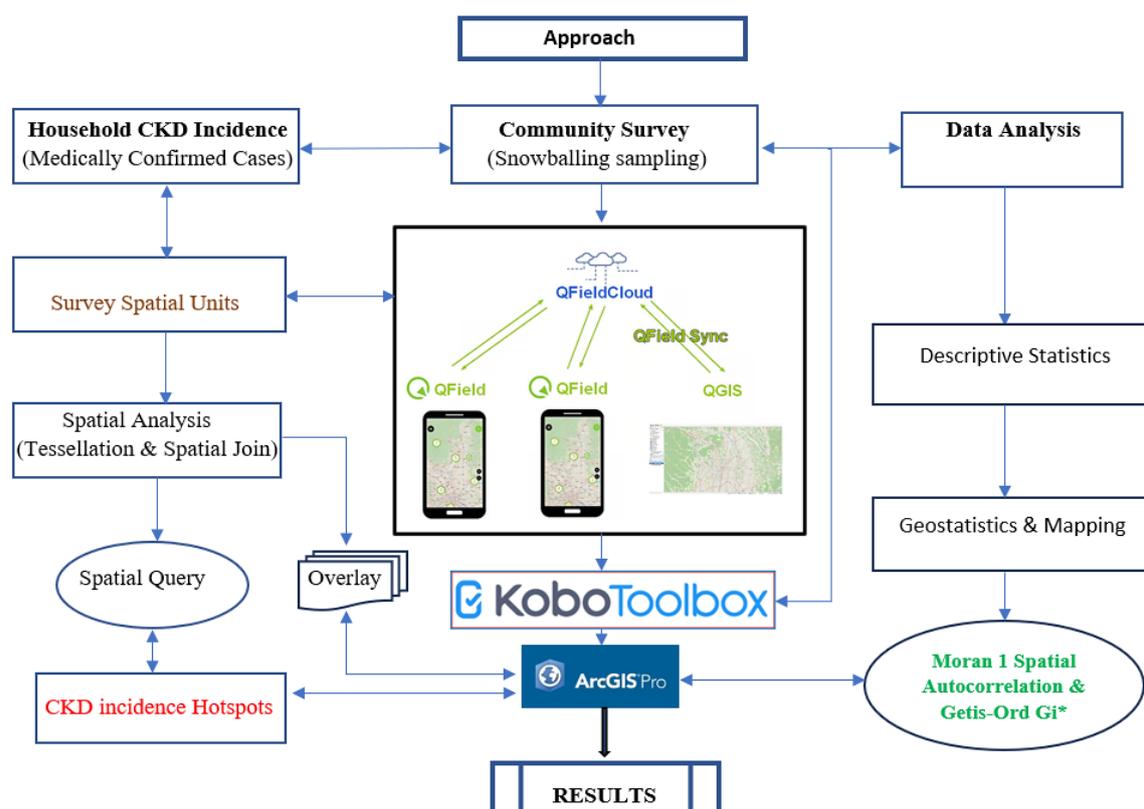


Figure 2: Methodology Flow Chart

The framework embedded local knowledge into both epidemiological and spatial data collection processes, enhancing data accuracy and contextual relevance.

Open-source GIS tools, QGIS, QField, and ArcGIS Pro 3.4, were used to map disease hotspots and analyse spatial patterns. Data were collected using electronic questionnaires deployed via the KoboToolbox platform, employing a snowball sampling method with the support of community leaders and household heads. Ethical approval was ensured through informed consent, and health-related information was collected alongside geographic coordinates for each identified CKD case. This integrated approach enabled spatial analysis of disease distribution and has been shown to be effective in low-resource, data-poor settings [36, 37].

#### Data Collection techniques

Data collection for this study was conducted using open-source digital tools to ensure accuracy, spatial integration, and field efficiency. Specifically, KoboToolbox was employed for administering electronic questionnaires, while QField was utilized for real-time geospatial data recording, survey area

delineation, and navigation support for field workers across the study sites.

KoboToolbox enabled the structured and efficient acquisition of data on diagnosed CKDu cases. A participatory, house-to-house survey approach was adopted to identify households with confirmed cases of chronic kidney disease (CKD). Inclusion criteria were strictly based on cases verified through medical documentation; households were requested to present medical records, which were checked to ensure data reliability. The field activities were preceded by a reconnaissance survey in Lawan Fannami Ward, which served to familiarize the research team with the terrain, community dynamics, and logistics. A total of six trained field workers conducted the main survey over a period of 28 consecutive days, ensuring full spatial coverage and community engagement throughout the data collection phase.

#### Case Identification and Sampling Technique

Households affected by CKD/CKDu or renal failure within the study area were identified using a snowball sampling approach. This method was considered appropriate due to the absence of centralized disease registries and geocoded health

records, the exploratory nature of the study, and the social sensitivities associated with the disclosure of chronic illness. Snowball sampling facilitated case identification through trusted community referrals, thereby improving access to diagnosed cases in a low-resource and potentially stigmatized context.

Recognizing that snowball sampling is inherently non-random and may introduce selection bias, particularly the over-representation of socially connected households and under-representation of isolated cases, specific measures were implemented to enhance methodological rigor. Recruitment was initiated concurrently across multiple wards with the support of community leaders to improve spatial coverage and reduce clustering driven solely by social networks. In addition, the study area was subdivided into predefined spatial units (polygons) derived from Enumeration Areas (EAs) established under the DLI 11.3 project. These spatial units were assigned to trained fieldworkers to guide household identification, minimize duplication of case reporting, and reduce spatial misrepresentation.

Case identification relied primarily on household self-reports of diagnosed renal failure and was corroborated, where available, using hospital records and patient hand cards. Given the non-clinical and spatial epidemiological focus of the study, cases were operationally classified as CKDu when no clearly stated clinical etiology, such as diabetes, hypertension, or hereditary kidney disease, was reported. Records with missing or uncertain diagnostic information were retained for spatial prevalence mapping but excluded from etiological interpretation to minimize misclassification bias.

Although some refusals were encountered, particularly among households hesitant to disclose health information, data integrity and spatial precision were maintained through GIS-enabled field coordination. Field assistants used the QField mobile application for real-time geospatial tracking of survey activities, ensuring clear demarcation of household coverage and systematic progress monitoring. As a result, duplication and over-reporting were minimized, and comprehensive spatial coverage of the study area was achieved despite fieldwork challenges. Overall, 441 confirmed CKDu cases were recorded across 430 surveyed households. Fieldworker assignments followed coded Enumeration Areas based on the

2022 Yobe State Geographic Information Service (YOGIS) property enumeration shapefile developed for the Disbursement Linked Indicator (DLI 11.3) project, as illustrated in Figure 3.

### **Spatial Data Analysis**

The study employed a tessellation approach to systematically divide the study area into regular, non-overlapping hexagonal spatial units. This method allowed for consistent spatial partitioning, facilitating the aggregation of CKDu cases within clearly defined boundaries for subsequent analysis. Each hexagonal grid covered an approximate area of 20,000 square meters (0.02 square kilometres or 4.9 acres), providing a uniform sampling framework across the study region. Treating each hexagon as a discrete sampling unit, the study enabled the standardized aggregation of household-level CKDu incidence data. A spatial join operation was performed to associate recorded CKDu cases with their corresponding hexagonal units, thereby enabling the systematic quantification of disease counts per standardized spatial area. This structured approach enhanced the uniformity of spatial comparisons, minimized potential sampling biases, and supported the identification of spatial clustering patterns of CKDu incidence across the study landscape (Figure 4).

To detect and evaluate the spatial patterns of CKDu prevalence, the study utilized Moran's I spatial autocorrelation as a key analytical tool. Moran's I is a statistical measure that determines whether the spatial distribution of disease cases across the study area is random, clustered, or dispersed. A positive Moran's I value signifies spatial clustering, indicating areas where cases are more concentrated, while a negative value suggests spatial dispersion, pointing to regions where cases are more spread out. Values near zero indicate random spatial patterns. For example, a Moran's I value of 0.1 implies weak but positive clustering, meaning that CKDu cases are somewhat closer to one another than would be expected by chance, though the clustering is modest. The statistical significance of Moran's I value was assessed through a permutation test involving multiple random simulations, ensuring that the observed spatial autocorrelation was not attributable to random chance. This analysis provided the foundation for understanding the broader spatial dynamics of CKDu incidence across the study area.

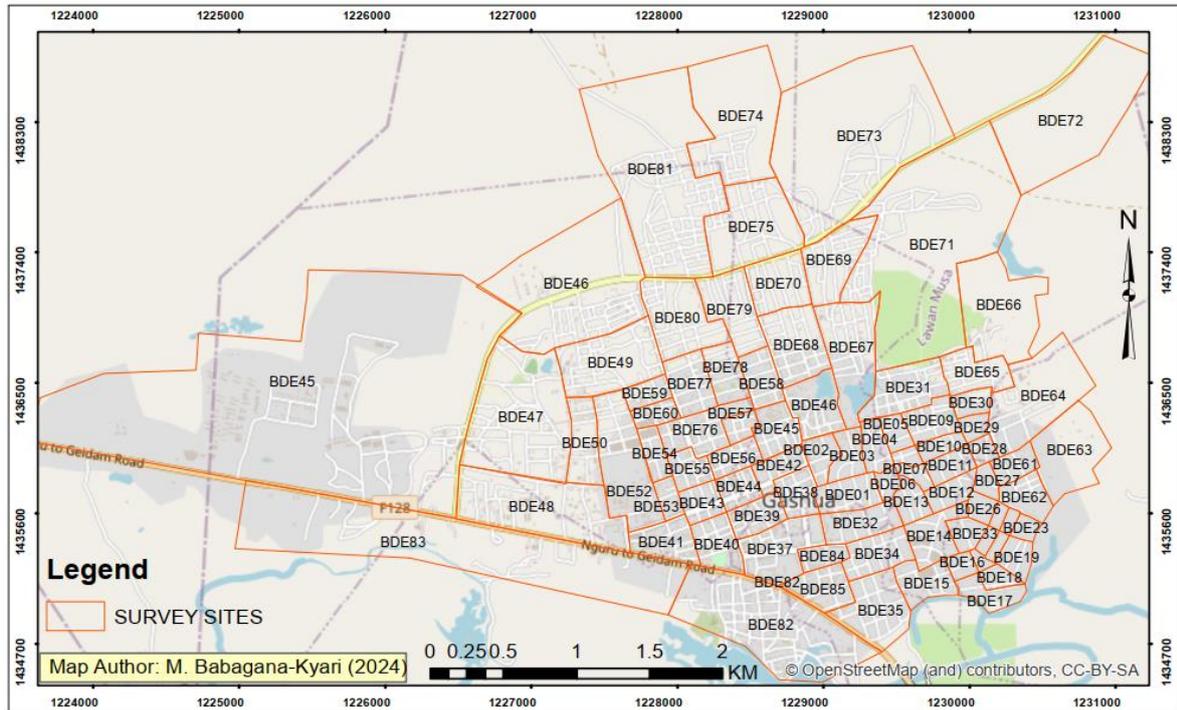


Figure 3: Survey blocks used in the Qfield App for field data collection

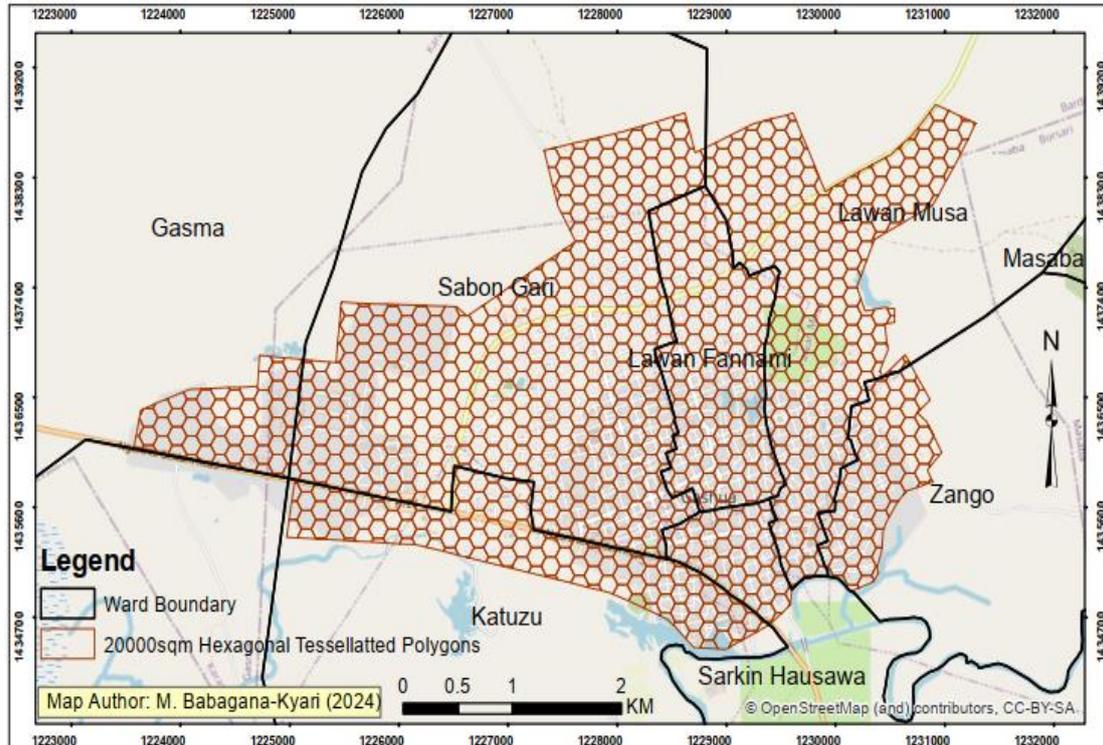


Figure 4: Tessellated polygons used for the disease incidence counts

### Hotspot Analysis Using Getis-Ord $G_i^*$

Following the spatial autocorrelation analysis, hotspot analysis was conducted using the Getis-Ord  $G_i^*$  statistic. This advanced spatial technique identifies statistically significant clusters by calculating z-scores for each spatial unit. Positive z-scores indicate hotspot areas with higher-than-expected CKDu incidence, while negative z-scores denote cold spot areas with lower-than-expected incidence. The magnitude of the z-score reflects the intensity and statistical confidence of the clustering. Higher absolute z-scores correspond to more statistically significant clusters. Through this method, three distinct and statistically significant CKDu clusters were identified within the study area, categorized into high, medium, and low prevalence zones. These spatial patterns are critical for identifying zones of elevated disease risk, which may be influenced by environmental exposures, socioeconomic factors, or other local determinants. The analysis highlighted specific locations warranting further in-depth investigation to better understand the underlying causes of disease concentration.

### Classification of Disease Prevalence

To facilitate meaningful interpretation of disease counts, geometric interval and standard deviation classification methods were employed. These classification schemes allowed for the stratification of CKDu prevalence into logical and analytically robust categories. By applying these methods, the spatial distribution of CKDu incidence was more clearly delineated, supporting a more intuitive understanding of disease intensity spatially across the study area.

### Statistical Analysis

Descriptive statistics, including frequency distributions, percentage calculations, and graphical representations such as bar charts, pie charts, and spatial maps, were performed using IBM SPSS Software version 19.0 to analyze the socio-demographic characteristics of CKD-affected households and capture perceptions of disease aetiology. As the study adopted a descriptive epidemiological design, the analysis focused on summarizing patterns and spatial distributions rather than conducting inferential statistical tests. No formal hypothesis testing (e.g., chi-square, t-tests, or regression analyses) was carried out; however, cross-tabulations were utilized to explore variations between categories for pattern identification. This approach was consistent with the study's objective of providing a comprehensive descriptive and spatial overview of CKDu prevalence in a low-resource setting.

## RESULTS AND DISCUSSION

### Spatial patterns of CKD incidence distribution

Figures 5 and 6 present the spatial distribution and clustering of Chronic Kidney Disease (CKD) incidences across the study area, analysed using the Getis-Ord  $G_i^*$  statistic to identify statistically significant spatial patterns. The results reveal distinct spatial clustering of reported CKD cases, with high-density hotspots prominently concentrated in the central parts of the study region. These hotspot areas represent locations with significantly elevated disease burden relative to their surroundings, indicating that CKD occurrence was spatially non-random. In contrast, cold spot areas, depicted in green, were characterized by low or negligible reported CKD incidence, suggesting fewer documented cases in these locations. Peripheral zones of the study area exhibit moderate to low incidence densities, which may reflect variations in population distribution, differences in exposure to potential risk factors, or reduced case identification in less densely settled areas. Although the observed clustering highlights clear spatial disparities in disease occurrence, the present analysis does not establish direct causal relationships between CKD incidence and specific environmental or socioeconomic determinants. Overall, the integration of spatial statistical analysis with community-derived data demonstrates the utility of GIS-based approaches for identifying disease concentration patterns in data-constrained settings. These findings support the use of spatial clustering outputs as an evidence base for guiding further epidemiological investigations and informing geographically targeted public health planning and resource allocation. Figure 7 illustrates the spatial statistics derived from Moran's I index, applied to analyze the patterns of chronic kidney disease (CKD) incidences in the study area. The results show a Moran's Index of 0.104632, with a z-score of 4.954559 and a p-value of 0.000001. Given the high z-score of 4.954559, there is less than a 1% probability that the observed clustering of CKD incidences occurred by random chance. This strong statistical evidence suggests the presence of non-random, spatially dependent factors influencing the distribution of CKD within the study area. The presence of these spatial clusters implies that the concentration of CKD incidences is not due to mere coincidence but may be driven by underlying environmental, socioeconomic, or health-related factors. Such clustering patterns highlight critical zones that warrant focused research attention, particularly groundwater quality exploration, as previous studies [30] implicated groundwater as a potential aetiology of the disease. Moreover, policymakers and health authorities can leverage these findings to prioritize environmental health surveillance and implement localized preventive strategies in high-risk zones.

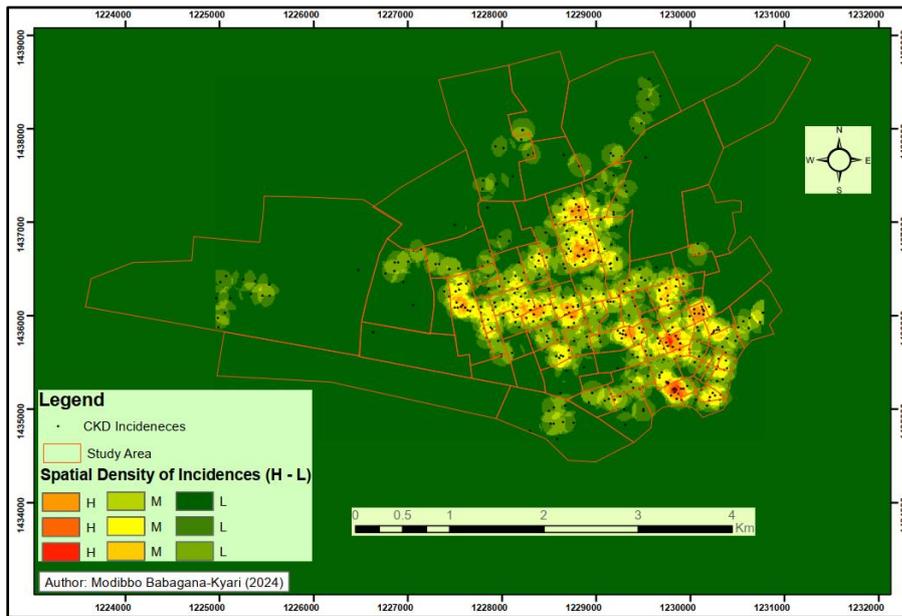


Figure 5: Spatial Distribution of CKDu Cases

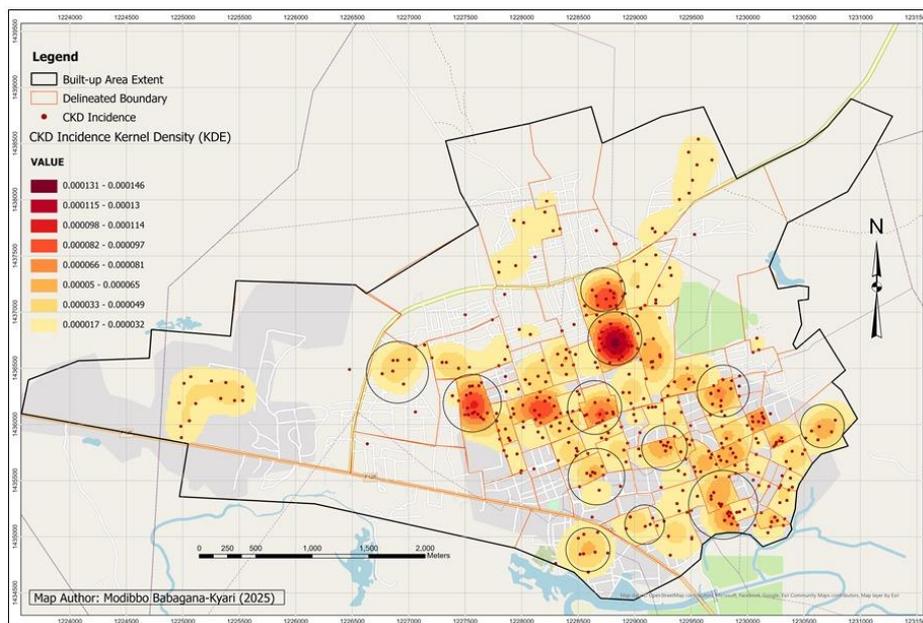


Figure 6: The identifiable hotspots of the disease in the area

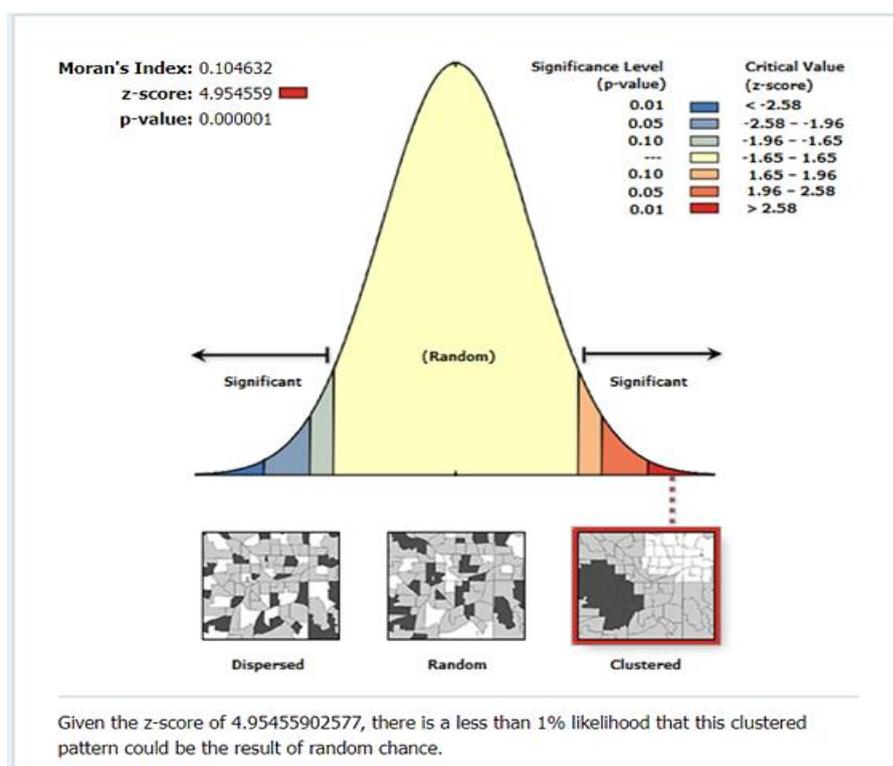


Figure 7: Spatial Statistics for incidence distribution over the area

According to Palaniyandi *et al* [37], the spatial clustering of diseases is oftentimes not merely coincidental, but rather influenced by underlying demographic, environmental, or lifestyle factors and occupational exposure factors. These factors can create conditions for disease prevalence, leading to observable patterns of clustering within specific geographic areas [38]. In the case of CKD, such clustering might be linked to localized environmental exposures, such as contaminated water sources, or specific behavioral or socioeconomic conditions, which warrant closer investigation to identify the root causes of the spatial distribution [39]. Therefore, the identified clustering pattern calls for further investigation into potential causes, such as water quality, lifestyle, or other localized risk factors that could be contributing to the uneven distribution of CKD in the study area. Exploring these factors is essential to understanding the underlying mechanisms driving the spatial concentration of CKD cases and to inform targeted public health interventions aimed at reducing the disease burden in hotspot areas.

The map in Figure 8 depicts the incidence of chronic kidney disease (CKD) across the surveyed area using hexagonal tessellation. Color coding is employed to differentiate between three levels of CKD hotspots. Dark red hexagons represent areas with the highest CKD incidence, indicating high

hotspots with values ranging from 7 to 10 cases. Medium hotspots, where CKD incidence is moderate (values of 3-6), are shown in lighter red. Low-incidence regions, referred to as cold spots, are illustrated with lighter red hexagons (values of 1-2). The survey area is delineated in grey, with hotspot classification performed using the geometric interval method in ArcGIS Pro 3.2. This classification technique is tailored for skewed data distributions, producing class boundaries that grow geometrically. It is particularly effective for handling unevenly distributed data, ensuring that each class remains visually distinct, even when values cluster at one end of the scale. By employing geometric progression, this method balances class sizes, making it well-suited for datasets that exhibit exponential growth or decline patterns.

This visual representation clearly delineates the spatial distribution of CKD, enabling the identification of areas with varying disease prevalence across the study area. Previously, Kang *et al* [40] have demonstrated practically that grid-based spatial modeling can be more effective than census tract approaches for measuring spatial distribution. Spatial tessellation is a powerful analytical approach for measuring the distribution of phenomena across space. This method has been applied to various diseases, including COVID-19, Newcastle disease, and bovine tuberculosis [41, 42].

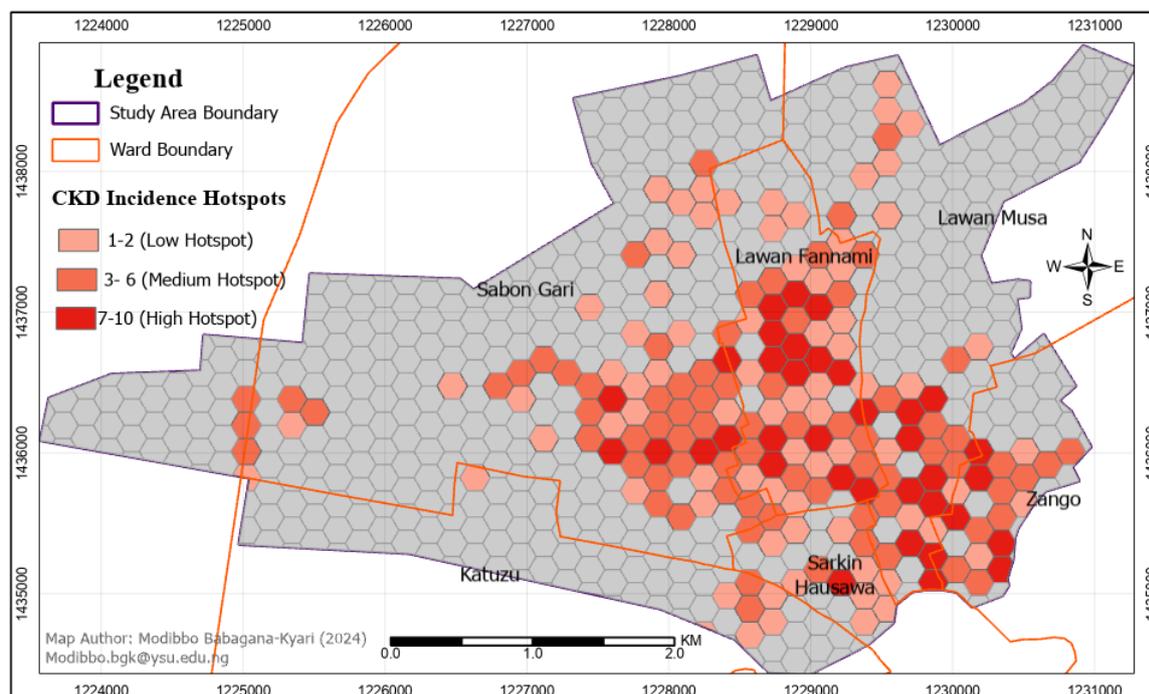


Figure 8: The three identified hotspots based on the spatial density of the incidence

### Spatial Distribution Analysis of the disease hotspots

Furthermore, to explore the spatial distribution of the disease incidence in greater depth, Figure 9 provides a clear depiction of chronic kidney disease (CKD) incidence across the study area, classified using the geometric standard deviation classification method in ArcGIS Pro, 3.2, which creates classes relative to the mean value by displaying standard deviations from the mean incidence rate as presented below. From the map, it can be seen that the regions are divided into three primary hotspots based on their deviation levels: high, medium, and low incidence areas. High-incidence hotspots, with a standard deviation greater than 2.5, reflect significantly elevated CKD cases compared to the average, indicating areas requiring urgent healthcare intervention and further research. Medium-incidence areas, with a standard deviation between 1.3 and 2.3, represent moderately elevated CKD rates. This tiered visualization highlights the gradient of disease distribution across the study area. This approach assesses the effectiveness of incidence distribution across hotspots by organizing data according to deviations from the mean, creating classes based on standard deviation intervals. It is especially appropriate for datasets that closely resemble a normal distribution, as it emphasizes the degree of deviation from the mean, providing a statistical insight into data variability. However,

while Freier *et al* [43] noted the limitations of this approach with skewed distributions, adjustments can be made to accommodate such data by applying transformations or alternative classification methods. These modifications can enhance the method's flexibility, allowing for more accurate representation of data with non-normal distributions, ensuring a broader applicability across various types of datasets.

### Basic profiles of the CKDu victims and their household characteristics

#### Consent for the study participation

During the survey, participants were informed that participation was entirely voluntary and that declining would incur no penalty. The findings indicate an overwhelmingly high level of willingness to participate, with consent obtained from nearly all surveyed households and only one respondent declining participation. This near-universal consent reflects strong community acceptance of the study and can be attributed to prior community sensitization, ethical approval from the State Ministry of Health Research Ethics Committee, and institutional support from the Bade Emirate, which facilitated trust and cooperation at the community level. Overall, the high consent rate underscores the effectiveness of the community-centric approach in fostering engagement among affected households.

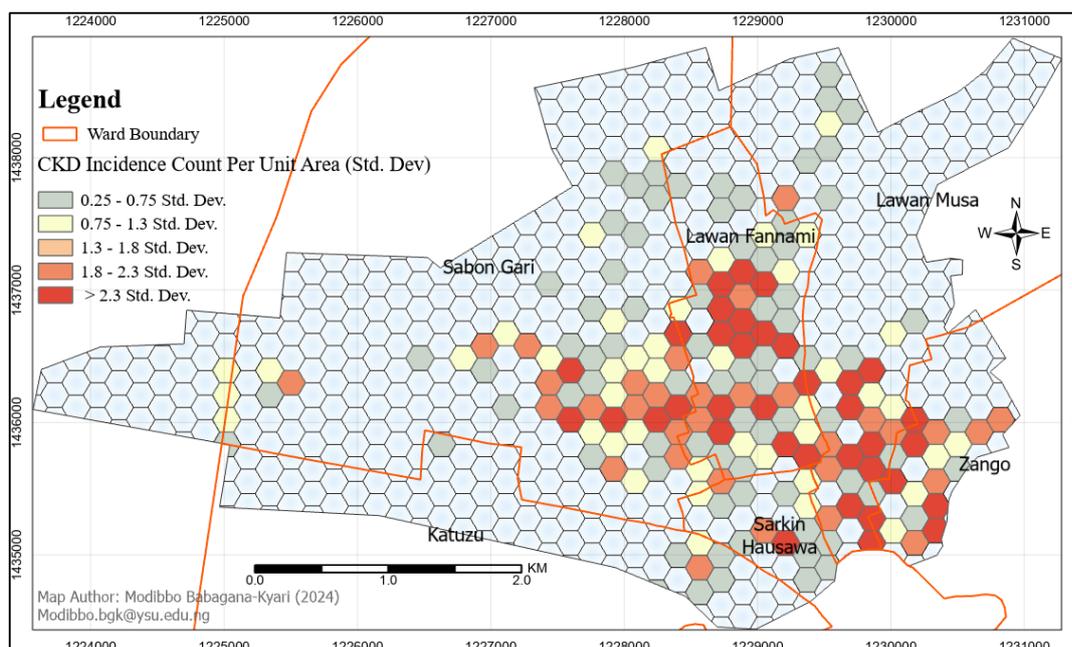


Figure 9: Depicting incidence rate distribution using standard deviation methods

### Household Respondents Characteristics

This section includes details such as age, gender, and marital status of the household respondent. The respondent is typically the individual whom the field assistants encountered during the survey in the victim's household. This aspect is necessary because the CKD victims may have passed away, been hospitalized, or been physically unable to participate in an interview during the survey.

### Respondent Status in household

Figure S1 provides a visual breakdown of respondent statuses. Notably, 37.44% of survey participants were household heads, while 51% were other household members. CKD patients comprised only 0.90% of respondents, suggesting a low representation likely due to mortality or morbidity. Nonetheless, household heads are considered reliable sources for healthcare information due to their comprehensive understanding of household affairs, as demonstrated by the recent study of [44].

### Age Group of the respondent

Figure S2 illustrates the age distribution. It is noteworthy that the majority of the respondents fall within the 35-44 years' age group, followed closely by those in the 25-34 years' age group. The next largest group is the 45-54-year age group. Understanding the age distribution of respondents is crucial for assessing the quality of the information collected in the context of the rampant CKD incidence survey. Notably, respondents under the age of 18 years constituted less than 5%

of the respondents, indicating a low representation of this age group. This also enhances the reliability of the data, as it was provided by mature adults within the surveyed households.

### Educational Level of the Respondent

Table 1 illustrates the educational profile of respondents who reported the incidence of household CKD. The data shows a variety of educational levels ranging from 'High Secondary School' to 'Postgraduate degree'. The majority of respondents have a high secondary school education (51.8%, 231). This is followed by individuals with informal education (16.8%, 72) and those with some college or a bachelor's degree (15.7%, 68). Lower percentages are noted in primary school education (6.5%, 28), Islamic education (4.4%, 19), and postgraduate degrees (2.8%, 12), highlighting a diverse educational background among the surveyed individuals. The total count of respondents is 430, accounting for 100% of the data presented in the table. The insights indicate that a significant percentage of respondents were literate, suggesting they fully understood the questionnaire used. Relatively, with 51.8% having completed high secondary school and 15.7% having some college or a bachelor's degree, the majority have a solid educational foundation. Research consistently demonstrates that individuals with higher levels of education tend to have higher response rates in health surveys [44]. Additionally, the presence of respondents with postgraduate degrees (2.8%)

highlights their literacy and comprehension levels. Gender of the respondent.

Table 2 illustrates the distribution of the gender of the respondents. From the data table, it can be seen that 81.6% were male while 14.8% were female. This is because the majority of the persons who participated in the study were house heads (HH) who were Males. The gender distribution of respondents in the CKD incidence survey provides significant context for understanding the demographics of those reporting household CKD incidences.

**Distribution CKD Incidence per Household**

The distribution of CKD incidence per household is illustrated to show how widespread the disease is within the study area. Table 3 presents the distribution of CKD incidences from the surveyed households. The data from Table 3 reveals that the majority of households surveyed in the study area, approximately 96.37%, have experienced one incidence of Chronic Kidney Disease (CKD). A smaller percentage, 3.62%, reported two incidences, indicating that while CKD is prevalent

within the community, multiple cases in the same household are relatively uncommon. The high percentage of households with single CKD cases suggests that CKD is a significant health concern, though it generally affects only one member of each household. This pattern may imply that genetic factors are not the primary cause of the disease, as multiple cases within families are rare.

To address this, interventions such as regular monitoring, educational programs, and lifestyle modifications could be implemented to help manage CKD more effectively in the community. However, early detection and regular health check-ups could also prevent the development of additional cases within the same household. However, the presence of multiple CKD cases in 2.46% of households may indicate the need for further investigation into potential genetic or environmental factors contributing to the disease. Understanding these influences could aid in developing more targeted and effective preventive measures, as highlighted by the recent study of [26] conducted across the region.

Table 1: Educational level of the respondent

Category	Frequency	Percentage (%)
High Secondary School	231	51.8
Informal Education	75	16.8
Some colleges/ Bachelor's degree	70	15.7
Primary School	29	6.5
Islamic education	18	4.0
Postgraduate degree	7	1.6
<b>Total</b>	<b>430</b>	<b>100.0</b>

Source: Researchers' Fieldwork (2023)

Table 2: Gender distribution of the household respondents

Category	Frequency	Percentage (%)
Male	364	81.6
Female	66	14.8
<b>Total</b>	<b>430</b>	<b>100.0</b>

Source: Researchers' Fieldwork (2023)

Table 3: Number of CKD incidence in households in the study Area

Options	Frequency	Percentage (%)
1 incidence	425	96.37
2 incidences	16	3.62
<b>Total</b>	<b>441</b>	<b>100.0</b>

Source: Researchers' Fieldwork (2023)

### Household Size

The size of the household indicates the density of persons within the household. Table 4 presents the household size, and it can be seen from the table that the category of households based on their sizes is in frequency and percentage. The largest category is "6-10 persons Household," representing 42.4% of the total surveyed households. This is followed by the "3-5 Person Household" category, which accounts for 21.7%, the "More than 10-person Household" category with 77 households representing 17.3%, the "1-Person Household" category with 53 households (11.9%), and the "2-person Household" category with 14 households (3.1%). In total, 430 households were surveyed. Thus, the data highlights the distribution of household sizes in the study area, which is crucial for understanding the context in which CKD incidence is being examined. The data suggest that the disease predominantly affects households of both larger and smaller sizes, and this household size may impact the management of CKD within the family due to the significant financial burden it imposes on them.

### Victims' household income

The section presents the distribution of incomes for the surveyed households. The histogram in Figure S3 represents the income distribution of households for chronic kidney disease (CKD) victims in CKD-affected areas. The Y-axis represents the frequency of the responses, while the X-axis represents the household incomes. The data is categorized into different income ranges, and the frequency of households falling into each income range is displayed. Additionally, the percentage of households in each category is shown on the bars.

The findings indicate that the majority of CKD-affected households fall within low- to moderate-

income categories, with over 75% earning less than ₦50,000 monthly. The most common income range was ₦20,000–₦50,000, accounting for approximately half of the surveyed households, while higher-income groups (₦100,000–₦200,000) were minimally represented. This distribution suggests that CKD prevalence is concentrated among economically disadvantaged households in the study area.

The observed income disparity may reflect differences in lifestyle and access to safe water sources. Higher-income households are more likely to invest in private boreholes or purchase bottled water, potentially reducing exposure to contaminated water—one of the suspected etiological factors of CKD. In contrast, lower-income households often depend on communal or untreated water sources, increasing vulnerability to waterborne contaminants. Empirical studies support this association, identifying low socioeconomic status as a key determinant of CKD/CKDu risk due to limited access to clean water, healthcare, and adequate nutrition [45, 46]. Additionally, poor water quality, particularly groundwater contamination by heavy metals and toxins, has been linked to elevated CKD prevalence [41]. Overall, the results highlight the economic vulnerability of CKD-affected households and its implications for health risk exposure and access to care.

### Medical Confirmation of Household CKD Incidence

As shown in Table 5, the vast majority of reported CKD cases were medically confirmed, with 98.1% (433 cases) validated by healthcare facilities, while only 1.8% (8 cases) lacked medical confirmation. Several households also presented medical reports during the survey, further supporting the credibility of the data.

Table 4: Surveyed Household Size

Responses	Frequency	Percentage (%)
6 -10 persons Household	189	42.4
3- 5 Persons Household	97	21.7
2 - person household	14	3.1
1- Person Household	53	11.9
More than 10-person Household	77	17.3
<b>Total</b>	<b>430</b>	<b>100.0</b>

Source: Researchers' Fieldwork (2023)

Table 5: Surveyed Household CKD Incidence

Response	Frequency	Percentage (%)
Yes	433	98.1
No	8	1.8
<b>Total</b>	<b>441</b>	<b>100.0</b>

Source: Researchers' Fieldwork (2023)

The high rate of medical confirmation indicates a strong level of diagnostic reliability among the surveyed cases, reducing concerns about underreporting or misidentification. This finding aligns with existing evidence emphasizing the importance of clinically verified diagnoses in accurately assessing CKD burden, particularly in low- and middle-income settings where under-diagnosis is common [43, 44]. Overall, the high verification rate strengthens confidence in the reported CKD prevalence and supports the robustness of the study’s findings.

**Family History of CKD Victims**

As presented in Table 6, the majority of households (73.3%; 343 out of 441) reported no known family history of CKD, while 18.2% (81 households) confirmed a family history. A small proportion of respondents (4.9%; 17 households) were uncertain and indicated that they could not recall.

The predominance of households without a known family history suggests that CKD occurrence in the study area may not be primarily driven by genetic factors but could instead reflect the endemic nature of the disease within the community. The widespread distribution of cases across unrelated households supports the plausibility of environmental or regional influences contributing to CKD prevalence. This interpretation aligns with previous studies that associate elevated CKD occurrence with local environmental conditions rather than hereditary predisposition [26]. Overall, the findings underscore the need for further investigation into non-genetic risk factors underlying CKD in the study area.

**CKD victim's status**

Table 7 presents data on the status of CKD (Chronic Kidney Disease) victims from the

surveyed households. The majority of the surveyed CKD victims, 75.96%, have died, indicating a high mortality rate among the respondents. In contrast, 22.9% of the surveyed patients are still alive, providing a perspective on the survival rate. Additionally, a small proportion of the surveyed individuals (1.13%) opted not to disclose their health status. While numerically minor, this non-disclosure may reflect underlying issues such as social stigma, fear of discrimination, or cultural sensitivities associated with chronic disease reporting. Such reluctance to share health information could impede accurate disease surveillance among the population. Recognizing and addressing these barriers is crucial for improving trust, data quality, and the inclusiveness of public health strategies aimed at CKD prevention and management, as well as other diseases. The survival rate among the respondents is relatively low, with only 22.9% of the patients still alive. This statistic provides a stark contrast to the high mortality rate and emphasizes the life-threatening nature of CKD. Additionally, a small portion of the surveyed individuals (1.13%) chose not to disclose their status, which, while a minor part of the dataset, indicates some level of privacy concern or stigma associated with the disease.

**Kidney Disease Type among Victims**

Table 8 illustrates the prevalence and types of kidney diseases among the participants. The data table below categorizes the diseases into six types: Glomerulonephritis, Kidney Stone/Kidney Cyst, Diabetic Kidney Disease, Kidney Infection, Hypertensive Nephropathy, and Complicated Cases. Additionally, there is a category for participants who had no clear idea about their type of kidney disease. This classification was obtained in relevant literature, hence was adopted and used.

Table 6: Households with a known Family History of CKD

Responses	Frequency	Percentage (%)
No	343	73.3
Yes	81	18.2
Can't recall	17	4.9
<b>Total</b>	<b>441</b>	<b>100.0</b>

Table 7: Statuses of CKD victims surveyed from the household

Patient Status	Frequency	Percentage (%)
Died	335	75.96
Alive	101	22.9
Preferred Not Say	5	1.13
<b>Total</b>	<b>441</b>	<b>100</b>

Source: Researchers’ Fieldwork (2023)

Table 8: Disease type among surveyed victims in the area

Disease Types	Frequency	Percentage (%)
a) Complicated case	135	30.61
b) Hypertensive CKD	109	24.71
c) Glomerunephritis	5	1.13
d) Kidney infection	61	13.83
e) Kidney Stone/Cyst	7	1.58
f) Diabetic Kidney Disease	19	4.30
g) No Idea about the disease Type	105	23.80
<b>Total</b>	<b>441</b>	<b>100.00</b>

Source: Researchers' Fieldwork (2023)

Table 8 shows that *complicated cases* constituted the largest proportion of reported CKD conditions (30.27%), while a substantial share of participants (24.66%) were uncertain about their specific disease type. In this study, *complicated cases* refer to individuals who were unable to clearly describe their condition or who were diagnosed with CKD after presenting with multiple coexisting health problems. This pattern suggests limited engagement in routine health monitoring within the community, leading to delayed diagnosis and compounded health conditions.

Hypertensive CKD accounted for 24.44% of cases, indicating a notable association between hypertension and kidney disease. Kidney infections represented 13.68% of reported conditions, while diabetic kidney disease was less common (4.26%). Other conditions, including kidney stones or cysts (1.57%) and glomerulonephritis (1.12%), were relatively rare. Overall, the high proportion of participants who were unsure of their disease type supports the operational classification of many cases as CKD of unknown etiology (CKDu). This diagnostic uncertainty underscores limitations in healthcare access and diagnostic capacity and highlights the need for improved community health education, early screening, and accessible diagnostic services to enable timely detection and management of chronic kidney disease.

### CKD Victim's Medical History

Table 9 provides a breakdown of the medical history of Chronic Kidney Disease (CKD) patients, categorizing their conditions with detailed counts and percentages. Hypertension emerges as the most prevalent condition, affecting 38.10% of the patients, while diabetes follows, present in 7.94% of cases. Combined conditions are also notable: 5.00% of patients reported both diabetes and hypertension, and 2.72% had both hypertension and diabetes, highlighting the frequent overlap of these risk factors in CKD cases. Other less common conditions include hepatitis (2.04%) and urinary tract infections (1.59%).

Notably, 41.89% of patients reported having "No Idea" about their medical history, indicating a lack of awareness or access to proper healthcare diagnostics, a common issue in CKD studies in resource-limited settings [43]. A small percentage (0.68%) preferred not to disclose their medical history. For instance, a study by [44] points to hypertension and diabetes as leading contributors to traditional CKD development, stressing the need for targeted interventions to manage these comorbidities in populations at risk. However, it remains unclear whether hypertension preceded or followed the CKD diagnosis, which is consistent with studies highlighting the bidirectional relationship between the two conditions [43].

Table 9: Medical History of CKD victims

History category	Frequency	Percentage (%)
1. Hypertension	168	38.10%
2. Diabetes	35	7.94%
3. Diabetes & Hypertension	22	5.00%
4. Hypertension & Diabetes	12	2.72%
5. Hepatitis	9	2.04%
6. Urinary Tract Infection (UTI)	7	1.59%
7. I have no Idea	185	41.89%
8. Preferred Not Say	3	0.68%
<b>Total</b>	<b>441</b>	<b>100.00</b>

Source: Researchers' Fieldwork (2023)

### **Victims' household perspectives on suspected risk factors**

Figure S4 presents community perceptions of suspected CKD risk factors from the perspective of victims' households. Contaminated water quality was the most frequently cited factor (30.8%), followed by perceptions attributed to the "Act of God" (20.5%) and witchcraft (8.6%). Other commonly mentioned factors included dehydration due to heat stress, abuse of analgesic drugs, diabetes prevalence, frequent use of herbal medication, and genetic factors, each accounting for approximately 6.8% of responses. Less frequently cited causes included consumption of vegetables grown locally (5.2%), lack of knowledge about risk factors (3.0%), and agricultural-related exposures such as food crops grown in the area (1.5%), agrochemical use (1.4%), and rice cultivation (0.5%).

The prominence of contaminated water quality highlights strong community concern regarding environmental exposures, although direct water quality assessment was not included in this study. This underscores the need for future research to prioritize water quality testing, particularly within identified high-incidence hotspots, to validate community perceptions and clarify potential etiological pathways. Similar associations between contaminated groundwater, particularly heavy metals such as cadmium and arsenic, and CKDu have been reported in studies from Sri Lanka and India [45]. The attribution of CKD to supernatural causes, such as the "Act of God" and witchcraft, reflects prevailing cultural interpretations in settings where biomedical understanding may be limited.

Furthermore, the notable reporting of heat stress-related dehydration and analgesic drug misuse aligns with global evidence linking CKDu to prolonged heat exposure and frequent use of non-steroidal anti-inflammatory drugs, both of which can exacerbate renal damage. Although agricultural factors were less frequently perceived by respondents, existing literature documents agrochemical exposure as a potential contributor to CKDu in farming communities. Overall, these findings illustrate the coexistence of environmental, behavioral, and cultural explanations of CKD within the community, reinforcing the need for integrated, multidisciplinary approaches to risk-factor investigation and intervention.

### **Implications for Public Health Interventions**

The identification of CKDu hotspots using the Open-source GIS technology with a community-centric approach offers critical insights, particularly the spatial distribution of the disease. Areas identified as hotspots should be prioritized for further investigation and intervention. Public health strategies should focus on improving water treatment infrastructure, regulating the use of agrochemicals, and increasing community awareness of CKDu risk factors, as previous studies implicated water contamination as a driver

of the disease in the area. Additionally, the integration of GIS with community-centric data collection can be used to monitor CKDu incidence over time, providing valuable information for early intervention and prevention efforts as well as insights for risk factors exploration.

### **Critical Reflection**

The integration of community-centric approaches with open-source GIS technologies represents a key strength of this study, enhancing community engagement, awareness of CKDu, and access to spatial health monitoring tools. The use of hotspot mapping effectively identified high-risk areas, providing practical insights to support targeted public health interventions in data-constrained settings.

However, the study also has limitations related to data quality and case identification. Information was often provided by household members on behalf of affected individuals, many of whom were deceased or medically incapacitated, resulting in reliance on morbidity and mortality data and potential reporting bias. While this may limit clinical precision, the focus on medically confirmed cases supported by hospital records in most households helped strengthen data reliability and mitigate uncertainties associated with second-hand reporting.

The study does not fully capture the complex, multifactorial etiology of CKDu, which likely involves interactions among environmental, occupational, lifestyle, and genetic factors. Future research should therefore adopt a multidisciplinary approach involving environmental chemists, nephrologists, toxicologists, epidemiologists, and public health professionals to enable a more comprehensive understanding and inform evidence-based interventions. Additionally, the context-specific nature of the findings may limit generalizability beyond the study area. Replicating this approach in ecologically and demographically diverse regions would help validate observed spatial patterns and assess the broader applicability of identified risk factors. Overall, the study contributes methodologically to understanding CKDu spatial prevalence in Northern Yobe State and provides a foundation for future research and targeted interventions.

### **Future Research and Policy Recommendations**

Further research is needed to investigate the specific environmental mechanisms contributing to CKD of unknown etiology (CKDu) in Northern Yobe State, with particular emphasis on groundwater contamination, chemical exposures, and the disease spatial prevalence. Groundwater quality assessments and geospatial analyses are essential for identifying environmental risk factors linked to CKDu in the region. To strengthen exposure-disease associations, future studies should also incorporate biomedical monitoring, such as blood or urine sample examination for a subset of the

population, providing direct evidence of internal exposure to nephrotoxic agents, particularly in groundwater and food resources, as their major pathways.

Equally, policymakers should prioritize investment in safe water infrastructure, particularly in high-risk communities. Key actors well-positioned to drive this initiative include the Yobe State Government, the Federal Ministry of Water Resources, and WASH sector programs operating at both national and sub-national levels. Additionally, efforts to enhance hospital record-keeping and tracking systems, particularly through geocoding of hospital data, would improve the ability to monitor CKDu and other environmentally induced diseases. This would not only benefit the affected communities in Northern Yobe State but the Country as a whole.

### CONCLUSION

This study demonstrates that Chronic Kidney Disease of unknown etiology (CKDu) in Northern Yobe State exhibits clear spatial clustering, with identifiable hotspots that reflect non-random disease distribution. The identification of these hotspots has direct public health relevance, as it provides an evidence base for prioritizing high-burden communities for targeted surveillance, environmental investigations, and preventive interventions. In settings where health resources are limited, such spatial intelligence is critical for guiding efficient allocation of healthcare services, risk communication, and environmental health assessments, particularly in relation to suspected exposures such as unsafe water sources and heat-related stress.

The findings further show that a community-driven, GIS-based approach can effectively generate spatially explicit disease evidence in data-poor contexts where formal disease registries and geocoded health records are unavailable. By integrating participatory data collection with open-source geospatial tools, this methodology enables early identification of high-risk areas and supports context-specific public health decision-making. Importantly, the approach is scalable and adaptable, making it suitable for application in other resource-limited regions facing similar challenges in disease surveillance and environmental health assessment. Overall, this study provides a practical framework for leveraging community participation and spatial analysis to strengthen CKDu surveillance, inform policy development, and guide targeted interventions in vulnerable populations.

### FUNDING

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. It is an independent scholarly investigation personally undertaken and entirely self-financed by the author.

### CONFLICT OF INTEREST

The authors declared no conflict of interest in this work.

### ETHICAL APPROVAL

Prior to the study, ethical approval was duly sought and granted by the Yobe State Ministry of Health's Research Ethics Committee, ensuring adherence to ethical guidelines for research involving human subjects. Additionally, informed consent was sought from all participants, with the assurance that their personal data would be anonymized and used strictly for research purposes, and all consented. The involvement of neighborhood leaders facilitated trust-building within the community, which was essential for the accurate reporting of CKDu cases.

### AUTHORS' CONTRIBUTION

M. Babagana-Kyari participated in the design of the study, data collection, GIS-based analysis, manuscript preparation, and final review. N. A Yaro provided guidance on the study design, supervised data analysis, reviewed and edited the manuscript, and contributed to the interpretation of findings. Similarly, K. M Yakasai participated in the supervision of data collection, provided critical input on methodology, reviewed the manuscript, and contributed to the final revisions.

### ACKNOWLEDGEMENT

I sincerely appreciate the Bade Emirate Council, the Yobe State Ministry of Health, and the Yobe State Geographic Information Service (YOGIS) for their invaluable support in providing the boundary map and shapefiles essential for this research.

### REFERENCES

- [1]. Rao IR, Bangera A, Nagaraju SP, Shenoy SV, Prabhu RA, Rangaswamy D, Bhojaraja MV. Chronic kidney disease of unknown aetiology: a comprehensive review of a global public health problem. *Trop Med Int Health*. 2023 Aug;28(8):588-600.
- [2]. Paidi G, Jayarathna AI, Salibindla DB, Amirthalingam J, Karpinska-Leydier K, Alshowaikh K, Ergin HE. Chronic kidney disease of unknown origin: a mysterious epidemic. *Cureus*. 2021 Aug 12;13(8). doi: <https://doi.org/10.7759/cureus.17132>
- [3]. Weaver VM, Fadrowski JJ, Jaar BG. Global dimensions of chronic kidney disease of unknown etiology (CKDu): a modern era environmental and/or occupational nephropathy? *BMC Nephrol*. 2015;16:1–8.
- [4]. Bradley M, Land D, Thompson DA, Cwierty DM. A critical review of a hidden epidemic: Examining the occupational and environmental risk factors of chronic kidney disease of unknown etiology (CKDu). *Environ Sci Adv*. 2024. doi: <https://doi.org/10.1039/D4VA00304G>
- [5]. Oladoyin V, Adetiloye O, Fatusi A. Assessment of routine health information

- system performance towards improvement of quality of reproductive, maternal, newborn, child and adolescent health services in Ondo and Ekiti States, Nigeria. *PLoS One*. DOI: <https://doi.org/10.1371/journal.pone.0318010>
- [6]. Adeleke IT, Adekanye AO, Onawola KA, Okuku AG, Adefemi SA, Erinle SA, et al. Data quality assessment in healthcare: a 365-day chart review of inpatients' health records at a Nigerian tertiary hospital. *BMJ Open*. 2012;2(6):e001234. doi: [10.1136/amiajn-2012-000823](https://doi.org/10.1136/amiajn-2012-000823)
- [7]. Iyun F. Limitations of using medical records for the spatial analysis of health problems in Nigeria. *Geogr Med*. 1985 January 1;15:122-40.
- [8]. Beyer KMM, Rushton G. Mapping cancer for community engagement. *Prev Chronic Dis* 2009;6(1).  
[http://www.cdc.gov/pcd/issues/2009/jan/08\\_0029.htm](http://www.cdc.gov/pcd/issues/2009/jan/08_0029.htm). (Accessed March 9, 2026)
- [9]. Chang AY, Parrales ME, Jimenez J, Sobieszczyk ME, Hammer SM, Copenhaver DJ, Kulkarni RP. Combining Google Earth and GIS mapping technologies in a dengue surveillance system for developing countries. *Int J Health Geogr*. 2009;8:1–1.
- [10]. Galarde-López M, Quiroz-Rocha GF, Candanosa-Aranda IE, Soberanis-Ramos O, García-García L. Community engagement in the diagnosis and control of a bovine paralytic rabies outbreak in two rural communities of Mexico. *J Agromedicine*. 2022;27(2):193–6.
- [11]. Galarde-López M, Quiroz-Rocha GF, Candanosa-Aranda IE, Soberanis-Ramos O, García-García L. Community engagement in the diagnosis and control of a bovine paralytic rabies outbreak in two rural communities of Mexico. *J Agromedicine*. 2022 April 3;27(2):193-6.
- [12]. Okeke, I. N., & Ihekweazu, C. (2021). The importance of molecular diagnostics for infectious diseases in low-resource settings. *Nat Rev Microbiol*, 19(9), 547-548. doi: <https://doi.org/10.1038/s41579-021-00598-5>
- [13]. Wongpituk K, Laosupap K, Butsorn A, Boonsang A, Thammaboribal P, Chankong W, Pokomnird C. Advancements in Disease Surveillance: The Role of GIS in Global Health Preparedness. *Int J Geo-Inf*. 2024 October 1;20(10). doi: <https://doi.org/10.52939/ijg.v20i10.3663>
- [14]. Musa GJ, Chiang PH, Sylk T, Bavley R, Keating W, Lakew B, Tsou HC, Hoven CW. Use of GIS mapping as a public health tool—from cholera to cancer. *Health Serv Insights*. 2013;6:HSI-S10471.
- [15]. Murad A, Khashoggi BF. Using GIS for disease mapping and clustering in Jeddah, Saudi Arabia. *ISPRS Int J Geo-Inf*. 2020;9(5):328. doi: <https://doi.org/10.3390/ijgi9050328>
- [16]. Figueroa-Solis E, Gimeno Ruiz de Porras D, Rojas-Garbanzo M, Whitehead L, Zhang K, Delclos GL. Prevalence and geographic distribution of self-reported chronic kidney disease and potential risk factors in Central America. *Int J Environ Res Public Health*. 2023;20(2):1308. doi: <https://doi.org/10.3390/ijerph20021308>
- [17]. Uzair M, Tariq S. Geographic Information System (GIS): A tool to manage vector-borne diseases. *Pak J Public Health*. 2023;13(1):1–2.
- [18]. Rydzanicz K, Hoffman K, Jawień P, Kiewra D, Becker N. Implementation of Geographic Information System (GIS) in an environment-friendly mosquito control programme in irrigation fields in Wrocław (Poland). *Eur Mosq Bull*. 2011;29:1–2.
- [19]. Rasam AR, Wahab NA, Ghazali R, Yusoff ZM. Integrating open-source GIS and Google Earth™ for managing rural waterborne outbreaks. In: 2014 IEEE 10th International Colloquium on Signal Processing and its Applications; 2014 March 7. IEEE. p. 62–6.
- [20]. Rasam AR, Noor AM. Contribution of GIS and remote sensing technologies for managing foodborne diseases in Malaysia. In: 2012 IEEE Control and System Graduate Research Colloquium (ICSGRC); 2012 July 16; Shah Alam, Malaysia. IEEE. p. 258–261. doi: [10.1109/ICSGRC.2012.6287172](https://doi.org/10.1109/ICSGRC.2012.6287172)
- [21]. Vlahos P, Schensul SL, Anand S, Shipley E, Diyabalanage S, Hu C, et al. Water sources and kidney function: Investigating chronic kidney disease of unknown etiology in a prospective study. *NPJ Clean Water*. 2021;4(1):50. doi: <https://doi.org/10.1038/s41545-021-00124-3>
- [22]. Botheju S, Dayananda N, Perera RT, Liyanage JA. Geospatial distribution of hydrological nephrotoxic characteristics in Kalawewa and Tissawewa reservoirs in Anuradhapura, Sri Lanka. *EQA Int J Environ Qual*. 2021;46:13–24.
- [23]. Ahmed SD, Agodzo SK, Adjei KA, Deinmodei M, Ameso VC. Preliminary investigation of flooding problems and the occurrence of kidney disease around Hadejia-Nguru wetlands, Nigeria, and the need for an ecohydrology solution. *Ecohydrol Hydrobiol*. 2018 Apr 1;18(2):212-24.
- [24]. Hamilton SA, Jarhyan P, Fecht D, Venkateshmurthy NS, Pearce N, Narayan KM, Ali MK, Mohan V, Tandon N, Prabhakaran D, Mohan S. Environmental risk factors for reduced kidney function due to undetermined cause in India: an environmental epidemiologic analysis. *Environ Epidemiol*. 2021 Oct 1;5(5):e170. doi:

- <https://doi.org/10.1097/EE9.000000000000170>
- [25]. Babagana-Kyari M, Kazeem MK, Jajere AA. The chronic kidney disease of unknown aetiology (CKDU) epidemics in northern Yobe state: The missing research gap. *Afr J Health Saf Environ.* 2022;3(2):31–45.
- [26]. Goni BW, Kwairanga HS, Abdu A, Ummate I, Abdu A, Ba'aba AI, et al. High burden of chronic kidney disease of unknown cause among patients receiving renal replacement therapy in Northeast Nigeria: A cross-sectional survey of haemodialysis units. *medRxiv.* 2024:2024-06.
- [27]. Ahmed SD, Agodzo SK, Adjei KA, Deinmodei M, Ameso VC. Preliminary investigation of flooding problems and the occurrence of kidney disease around Hadejia-Nguru wetlands, Nigeria, and the need for an ecohydrology solution. *Ecohydrol Hydrobiol.* 2018;18(2):212–24.
- [28]. Jajere AA, Sawa AB, Kibon UA, Muhammed BU, Babagana-Kyari M. Spatio-temporal variability analysis of rainfall in Kumadugu-Yobe River Basin, Nigeria. *Geosfera Indones.* 2022;7(1):18–41.
- [29]. Vlahos P, Schensul SL, Anand S, Shipley E, Diyabalanage S, Hu C, et al.
- [30]. Water sources and kidney function: Investigating chronic kidney disease of unknown etiology in a prospective study. *npj Clean Water.* 2021;4(1):50. doi: 10.1038/s41545-021-00124-3.
- [31]. Ahmed SD, Agodzo SK, Adjei KA, Deinmodei M, Ameso VC. Preliminary investigation of flooding problems and the occurrence of kidney disease around Hadejia-Nguru wetlands, Nigeria, and the need for an ecohydrology solution. *Ecohydrol Hydrobiol.* 2018;18(2):212–24.
- [32]. Waziri M, Ogugbuaja VO. Interrelationships between physicochemical water pollution indicators: A case study of River Yobe, Nigeria. *Am J Sci Ind Res.* 2010;1(1):76–80.
- [33]. Badejo BI, Abubakar KA, Zira JD, Enoch BB. Assessment of physicochemical parameters of River Yobe, Gashua, Yobe State, Nigeria. *Int J Fish Aquat Stud.* 2017;5(2):93–8.
- [34]. Naibbi A, Baily B, Healey RG, Collier P. Changing vegetation patterns in Yobe State, Nigeria: An analysis of the rates of change, potential causes, and the implications for sustainable resource management. *Int J Geosci.* 2014;5:50–62.
- [35]. Alkali AG. River-aquifer interaction in the Middle Yobe River Basin, North East Nigeria. 1995. Available from: <https://core.ac.uk/download/pdf/29409501.pdf>
- [36]. Dawoud MA, Raouf ARA. Groundwater exploration and assessment in rural communities of Yobe State, Northern Nigeria. *Water Resour Manag.* 2009;23:581–601.
- [37]. Fornace KM, Surendra H, Abidin TR, Reyes R, Macalinao ML, Stresman G, et al. Use of mobile technology-based participatory mapping approaches to geolocate health facility attendees for disease surveillance in low-resource settings. *Int J Health Geogr.* 2018;17:1–0. doi: <https://doi.org/10.1186/s12942-018-0141-0>
- [38]. Palaniyandi M, Anand PH, Maniyosai R. GIS-based community survey and systematic grid sampling for dengue epidemic surveillance, control, and management: A case study of Pondicherry Municipality. *Int J Mosq Res.* 2014;1(4):30–8.
- [39]. Osei FB, Duker AA, Stein A. Evaluating spatial and space-time clustering of cholera in Ashanti-Region-Ghana. In: *Cholera.* IntechOpen; 2012. p. 19–32.
- [40]. Waller LA. Spatial clustering and autocorrelation of health events. In: *Handbook of Regional Science.* Springer Berlin Heidelberg; 2021. p. 2035–51.
- [41]. Kang SY, McGree J, Baade P, Mengersen K. An investigation of the impact of various geographical scales for the specification of spatial dependence. *J Appl Stat.* 2014; 41(11):2515–38.
- [42]. Perez L, Dragicevic S. An agent-based approach for modeling dynamics of contagious disease spread. *Int J Health Geogr.* 2009;8:1–7.
- [43]. Liu R, Yang H. Spatial tessellation of infectious disease spread for epidemic decision support. *IEEE Robot Autom Lett.* 2021;7(1):626–33.
- [44]. Freier JE, Miller RS, Geter KD. Geospatial analysis and modeling in the prevention and control of animal diseases in the United States.
- [45]. Bojola F, Dessu S, Dawit Z, Alemseged F, Tessema F. Assessment of health care seeking behavior among household heads in Dale Woreda, Sidama Zone, Southern Ethiopia. *Glob J Med Res.* 2018;18(1):19–29.
- [46]. Stanifer JW, Muiru A, Jafar TH, Patel UD. Chronic kidney disease in low- and middle-income countries. *Nephrol Dial Transplant.* 2016;3 (6):868–74.
- [47]. Chang KY, Wu IW, Huang BR, Juang JG, Wu JC, Chang SW, et al. Associations between water quality measures and chronic kidney disease prevalence in Taiwan. *Int J Environ Res Public Health.* 2018;15(12):2726. doi: [10.3390/ijerph15122726](https://doi.org/10.3390/ijerph15122726)